Logistic Regression

In [1]: import pandas as pd
import seaborn as sns
import warnings

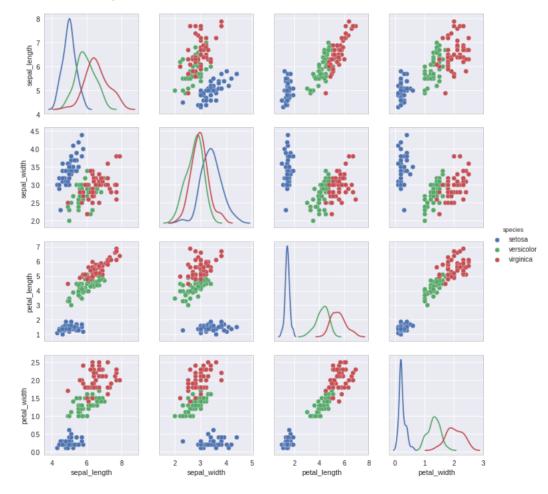
warnings.filterwarnings('ignore')
% matplotlib inline

In [2]: iris = sns.load_dataset('iris')
iris.sample()

Out[2]:sepal_lengthsepal_widthpetal_lengthpetal_widthspecies1057.63.06.62.1virginica

In [3]: sns.pairplot(iris, hue = 'species', diag_kind = 'kde')

Out[3]: <seaborn.axisgrid.PairGrid at 0x7f405116fac8>



In [4]: from sklearn.preprocessing import LabelEncoder

```
In [5]: columns = ['petal_length', 'species']
    species = ['setosa', 'versicolor']

data = iris[columns]
    data = data.loc[data['species'].isin(species)]
```

In [6]: data.head(5)

Out[6]:

	petal_length	species
0	1.4	setosa
1	1.4	setosa
2	1.3	setosa
3	1.5	setosa
4	1.4	setosa

In [7]: data.tail(5)

Out[7]:

	petal_length	species
95	4.2	versicolor
96	4.2	versicolor
97	4.3	versicolor
98	3.0	versicolor
99	4.1	versicolor

In [9]: data.head(5)

Out[9]:

	petal_length	species
0	1.4	0
1	1.4	0
2	1.3	0
3	1.5	0
4	1.4	0

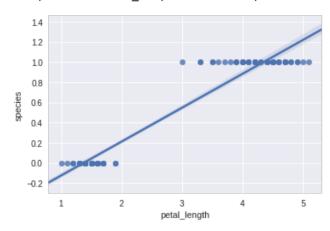
In [10]: data.tail(5)

Out[10]:

	petal_length	species
95	4.2	1
96	4.2	1
97	4.3	1
98	3.0	1
99	4.1	1

```
In [11]: sns.regplot(x = 'petal_length', y = 'species', data = data)
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3ffee63b38>

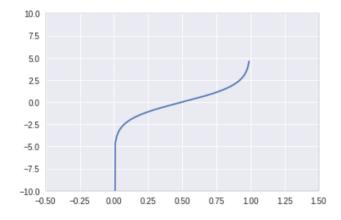


```
In [12]: import numpy as np import matplotlib.pyplot as plt
```

```
In [13]: def logit(x):
    return np.log(x) - np.log(1 - x)
```

```
In [14]: x = np.arange(-1, 1, 0.01)
    ax = plt.gca()
    ax.set_xlim([-0.5, 1.5])
    ax.set_ylim([ -10, 10])
    plt.plot(x, logit(x))
```

Out[14]: [<matplotlib.lines.Line2D at 0x7f3ffc851588>]



```
In [15]: def logistic(x, max = 1, mid = 0.5, steepness = 1):
    return max / (1 + np.exp(-steepness * (x - mid)))
```

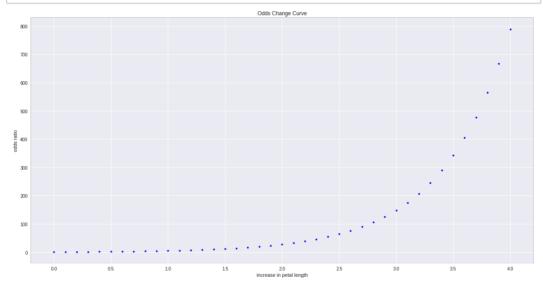
```
In [16]: x = np.arange(-6, 6, 0.01)
          plt.plot(x, logistic(x))
Out[16]: [<matplotlib.lines.Line2D at 0x7f3ffc7aae80>]
          10
          0.8
          0.4
          0.2
           0.0
              -6
                           -2
                                              4
In [17]: from sklearn.linear_model import LogisticRegression
In [18]: | X = np.reshape(data['petal length'], (len(data['petal length']), 1))
          y = np.reshape(data['species'], (len(data['species']), 1))
          lr = LogisticRegression()
          lr.fit(X, y)
Out[18]: LogisticRegression(C=1.0, class weight=None, dual=False, fit intercept=Tr
                    intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                    penalty='\overline{\infty}2', random_state=None, solver='\overline{\infty}1blinear', to\overline{\infty}=0.0001
                    verbose=0, warm start=False)
In [19]: beta0 = lr.intercept_[0]
          beta0
Out[19]: -4.1939275042884923
In [20]: beta1 = lr.coef [0,0]
          beta1
Out[20]: 1.6673009365067675
In [21]: def predict_prob(x):
              exponent = np.exp(beta0 + beta1 * x)
              return exponent / (1 + exponent)
In [22]: def odds(x):
              return x / (1 - x)
In [23]:
          import prettytable as pt
          from IPython.core.display import display, HTML
```

```
In [24]: table = pt.PrettyTable(['petal_length', '$\hat{p}$', '$1 - \hat{p}$$', '
odds'])
sample = pd.concat([data['petal_length'].head(5), data['petal_length'].t
ail(5)])

for i in sample:
    p = np.round(predict_prob(i), 2)
    table.add_row([i, p, 1 - p, odds(p)])

display(HTML(table.get_html_string()))
```

petal_length	\hat{p}	$1 - \hat{p}$	odds
1.4	0.13	0.87	0.149425287356
1.4	0.13	0.87	0.149425287356
1.3	0.12	0.88	0.136363636364
1.5	0.16	0.84	0.190476190476
1.4	0.13	0.87	0.149425287356
4.2	0.94	0.06	15.6666666667
4.2	0.94	0.06	15.6666666667
4.3	0.95	0.05	19.0
3.0	0.69	0.31	2.22580645161
4.1	0.93	0.07	13.2857142857



In [27]: print('petal length being either setosa or versicolor: ', -beta0/beta1)

petal length being either setosa or versicolor: 2.51539923745